Hedging Credit: Equity Liquidity Matters

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Abstract

We theorize and confirm a new channel by means of which liquidity costs are embedded in CDS spreads. We show that credit default swap (CDS) spreads are directly related to equity market liquidity in the Merton (1974) model via hedging. We confirm this relationship empirically using a sample of 1,452 quarterly CDS spreads over 2001-2005. In the model, this relationship is monotone increasing when credit quality worsens. These results are robust to alternative measures of equity liquidity and other possible determinants of CDS spreads.

Key words: credit default swap, basis, liquidity
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1. Introduction

A growing literature documents that illiquidity is a component of bond spreads. For instance, the "spread puzzle" where the spread between corporate bonds and Treasuries is too high to be explained by credit related factors (Collin-Dufresne, Goldstein and Martin (2001), Huang and Huang (2003)) has been attributed mostly to illiquidity in the bond markets. Furthermore, credit risk is now being traded using credit default swaps (CDS) and the CDS-bond basis (the difference between the CDS spread and the bond yield) has been shown to be related to liquidity proxies (Longstaff, Mithal and Neis (2005), Mahanti, Nashikkar and Subrahmanyam (2007)). Hence the trading of credit risk through corporate bonds results in bearing liquidity risk.

In contrast to bond spreads, the natural assumption in the literature has been that CDS spreads contain minimal or no components of liquidity, and to a lesser extent, other non-default priced systematic risks. We investigate this assumption theoretically and empirically. The paper makes explicit the theoretical link between CDS spreads and illiquidity in the equity of the reference entity in the context of Merton (1974)'s structural model. We take the theoretical predictions of the model to the data using a final sample of 1,452 quarterly CDS spreads from 2001-2005 and find that the equity liquidity of the reference entity is negatively related to CDS spreads. These results are robust to different measures of liquidity and to other known determinants of CDS spreads. We believe this is the first paper to establish a link between CDS spreads and liquidity in the equity markets.[2] Thus, this paper extends the literature which examines the role of liquidity in credit markets and the literature on explaining the cross-section of CDS spreads (see the papers by Berndt, et al. (2003), Ericsson, Jacobs and Oviedo (2005), Das, Hanouna and Sarin (2006), Duffie, Saita and Wang (2007)).

There is an inherent dissimilarity between liquidity in corporate bonds and CDS liquidity based on differences in the market's use of these instruments. Whereas the average corporate bond does not trade frequently[3], and is held for portfolio reasons, default swaps are widely used in credit arbitrage, construction of CDOs, and risk management. Therefore, even though there is a literature on liquidity effects in bond spreads (see Chen, Lesmond and Wei (2007), Goldstein, Hotchkiss and Sirri (2006)), it is necessary to investigate the same phenomenon separately in the CDS markets. The sellers of CDS contracts actively hedge their exposures through the equity markets and through the use of options and debt-related instruments. When liquidity in the equity markets dries up, it becomes more expensive for sellers of CDS contracts to delta hedge their short credit positions by taking short positions in equity or long positions in put options. These hedging costs are recovered through higher CDS spreads, even when illiquidity is not systematic. Indeed, our empirical results confirm that equity market illiquidity remains a strong explanatory variable for CDS spreads even after controlling for other default related factors.

That liquidity is priced as a factor has been established for equity markets in prior work, such as that of Acharya and Pedersen (2005). Equity market illiquidity is priced into bond spreads, as shown in de Jong and Driessen (2005). These papers examine overall market illiquidity in equity and bond markets. Other work looks at liquidity in individual securities. For example, Chen, Lesmond and Wei (2007) examine bond-specific illiquidity using bond market measures, but do not consider equity market linkages. In a similar manner, our work here focuses particularly on explaining the cross-section of CDS spreads with liquidity measures on individual names. This paper is not focused on whether illiquidity is a priced factor in default swap markets. The hedging mechanism implies that transaction costs are transmitted into spreads even when this risk is not systematic, in the same manner in which default likelihoods are components of spreads. There may be additional liquidity premia arising from correlated risks in CDS spreads, suggested in the work of Acharya, Schaefer and Zhang (2007), but this is not the focus of our investigation.

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[2] In related work de Jong and Driessen (2005) present evidence that *overall* equity market illiquidity is related to liquidity premia in *corporate bond* spreads.

[3] The median bond trades only once a year.

Unlike the past literature, we focus on the mechanism for the transmission of illiquidity from equity markets to CDS spreads. We posit that, since CDS contracts are actively hedged, unlike bonds, and because hedging costs are incurred whether or not liquidity risk is systematic, we should anticipate that illiquidity costs from the equity markets are transmitted into CDS spreads. Using standard measures of illiquidity and transactions costs in the *equity* markets, such as the ILLIQ measure of price impact of Amihud (2002), the LOT measure of Lesmond, Ogden and Trzcinka (1999), and bid-ask spreads, regressions show that individual variations in illiquidity across firms explain the cross-section of CDS spreads even after controlling for default and other explanatory variables.[4] By controlling for common time-series effects across firms, we isolate the firm-specific component of the impact of equity market illiqidity on CDS spreads.

There is also growing evidence that default risk and liquidity risk are correlated. Acharya, Schaefer and Zhang (2007) present a model where declining credit quality results in the drying up of liquidity in the corporate debt markets. Similar relationships are observed in Downing, Underwood and Xing (2007). Credit spreads and illiquidity are positively correlated in the empirical record. In this paper, we present a model in which such an effect is theoretically supported at the level of individual credit names. Upon testing, this theoretical proposition is also found to be supported by the data, i.e. liquidity components increase as the credit risk of an individual issuer increases. Thus, our theoretical and empirical results complement those of the literature.

The rest of the paper proceeds as follows. The model in Section 2 establishes the link between equity market illiquidity and CDS spreads via a hedging mechanism. It also posits that the impact of illiquidity in the equity markets on CDS spreads will increase when credit quality worsens. This relationship is monotone and convex. These relationships are tested in Section 3, where we also present the data and the variables used in the study. The results confirm the theoretical predictions. Section 4 provides concluding comments.

2. Hedging CDS in a Structural Model

Ericsson and Renault (2006) develop a structural model to connect bond market liquidity with default risk. In their model, bond spreads are related to costs of having to trade when it is not optimal to do so. Random liquidity shocks force suboptimal bond trades resulting in potential reductions in value of the bonds. This cost is embedded in bond spreads. Hence bond illiquidity is related to the lack of immediacy in liquidating a bond position (see Chacko (2005), Chacko, Jurek and Stafford (2007) for more evidence on lack of immediacy).

Our model is similar to that of Ericsson and Renault (2006) in that it is also based on a structural model. However, there are two differences. First, Ericsson and Renault examine the connection of liquidity and default risk for bonds, whereas our paper connects default risk and equity illiquidity in CDS contracts. Second, the mechanism for illiquidity transmission in our paper is hedging, whereas other work is mainly focused on the lack of immediacy.

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[4] Bessembinder, Maxwell and Venkataraman (2005) examine liquidity and price impact in corporate bonds, and Goldstein, Hotchkiss and Sirri (2006) consider transaction costs in the same markets.

We begin by positing the standard Merton (1974) framework for default risk, in that firm value V is assumed to follow a geometric Brownian motion under the risk-neutral measure:

$$dV = rV\ dt + \sigma V\ dW \tag{1}$$

where r is the risk free rate and σ is the volatility of the firm's assets; dW is the standard Wiener increment. It is well-known that in this framework, stock value S is determined as a call option on the firm's value V, with strike price equal to the face value F of zero-coupon debt (of maturity T) issued by the firm. Hence,

$$S = V\ \Phi(d_1) - Fe^{-rT}\ \Phi(d_2) \tag{2}$$

$$d_1 = \frac{\ln(V/F) + (r + \sigma^2/2)T}{\sigma\sqrt{T}} \tag{3}$$

$$d_2 = \frac{\ln(V/F) + (r - \sigma^2/2)T}{\sigma\sqrt{T}} \tag{4}$$

where $\Phi(x)$ is the cumulative normal distribution value for x.

We consider a very simple insurance contract where the seller is obligated to make good a pre-specified loss amount on default of the firm. For simplicity, assume that the maturity of the insurance contract is T, the same as that of the firm's debt. This is analogous to a very simple CDS contract where the buyer pays only an upfront premium in return for a fixed contingent payment on default. Denoting the price of the contract as C, the price is proportional to the risk-neutral probability of default, which in the Merton model is simply $\Phi(-d_2)$.

The seller of this CDS hedges credit risk by taking a short equity position, either by selling stocks or buying put options, because the value of the CDS contract declines when the stock price rises, i.e. the hedge ratio is negative, $\Delta = \frac{\partial C}{\partial S} \leq 0$. Note also that as Δ changes, the seller adjusts the amount of equity shorted as a hedge. Implementation of the initial hedge, changes in the hedge ratio, and the close out of the hedge, all result in hedging costs emanating from frictions in the equity markets. Hedging costs are proportional to the size of Δ, which may be computed in closed-form as follows:

$$\begin{aligned}\Delta &= \frac{\partial C}{\partial S} \\ &= \frac{\partial C}{\partial V} \times \frac{\partial V}{\partial S} \\ &= \frac{\partial}{\partial V}\Phi(-d_2) \times \frac{1}{\Phi(d_1)} \\ &= -\phi(-d_2)\frac{\partial d_2}{\partial V} \times \frac{1}{\Phi(d_1)} \\ &= \frac{-\phi(d_2)}{\Phi(d_1)}\ \frac{1}{V\sigma\sqrt{T}} \quad \leq 0 \end{aligned} \tag{5}$$

where $\phi(x)$ is the normal density of x. We can also see that this confirms that the relationship of CDS to equity (or firm value) is an inverse one. Using the equation above, Figure 1 shows that as the stock price falls, the absolute hedge ratio rises, thereby increasing hedging costs proportionately. We note that in addition to selling equity to hedge a short CDS position, the seller of the CDS may trade in options by buying puts or selling calls (see the paper by Carr and Wu (2007) for the connection between default swaps and equity options). The risk may also be laid off by shorting the underlying reference bonds. Hence, liquidity in these other markets may also impact CDS spreads. In the context of the Merton model however, these products are linked to the equity of the firm, and the sign of the hedging relationship remains the same as shown in the analytic result above. Further, in a portfolio context, where cross-hedging is achieved, the magnitude of this effect will be mitigated, and would bias the results against the findings of the paper.

Hedging costs, proportional to Δ, may arise from various frictions in the equity markets. We examine three well-known liquidity frictions here. *First*, price impact from illiquidity, which we proxy with the ILLIQ measure of Amihud (2002). The greater the hedging need, it is likely to create a larger price impact, making this proxy for illiquidity a good candidate variable for explaining CDS spreads. *Second*, lack of immediacy in the equity markets increases hedging costs (see Chacko, Jurek and Stafford (2007)) or non-tradability of the stock, proxied by the zero-return (LOT) measure of Lesmond, Ogden and Trzcinka (1999). Here, hedging costs arise from the fact that this form of illiquidity might result in slippage in the dynamic hedging program, either through delayed hedging or partial hedging. *Third*, bid-ask spreads. The wider the bid-ask spreads, the greater the round trip cost of putting on the hedge and taking it off when the credit position is closed out. We note that all three measures of illiquidity impact the costs of the dynamic hedging strategy, albeit through slightly different channels. There are two other aspects of dynamic hedging that impact running a CDS book irrespective of which illiquidity channel we consider most impacting. One, dynamic hedging incurs greater costs when markets are volatile as the hedge ratio changes more rapidly.[5] Since changes in volatility are likely to be systematic, it is hard to diversify this component of hedging risk. Two, when credit quality changes, even for a single issuer, re-hedging across positions in the market occurs on one side of the bid-ask spread, and hence, the costs of adverse selection are exacerbated. Both these effects enhance the impact of equity market illiquidity on CDS spreads.

In the next section, we describe our data and provide an empirical analysis that demonstrates that CDS spreads are explained by equity market liquidity frictions, and that this component increases as credit quality worsens.

3. Empirical Testing

3.1. *Data*

Our sample of credit default swap spreads is obtained from Bloomberg. It consists of 2,860 quarterly credit default swap spreads over the period 2001-2005. This sample was further restricted to include only CDS securities where the notional value is dollar denominated and where the reference entity is a publicly traded firm. We further restricted the sample to CDS contracts of five-year maturity as these are the most actively traded maturity. Financial information on the reference entity is then obtained from COMPUSTAT and CRSP. These restrictions atrophy the data to 1,452 quarterly spreads. Berndt, et al. (2003) find that a large portion of the variation in CDS spreads can be explained by the distance-to-default and the T-bill rate. In addition, Das, Hanouna and Sarin (2006) find that certain accounting ratios can explain CDS spread variation above and beyond the distance-to-default metric and the T-bill rate. We use both sets of variables to control for default risk and then include the liquidity variables to ascertain their influence.

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[5] This suggests another channel for increase in credit spreads. As shown by Leland (1985), increases in transactions costs may be reflected as increases in option volatility. In the credit setting increases in volatility result in higher credit spreads. Our regressions in the empirical section show that volatility is positively related to credit spreads. Thanks to S. Viswanathan for pointing out this interesting connection.

In the following subsections we explain how we proxy for liquidity, how we calculate the distance-to-default and finally, describe the computation of the accounting ratios used as explanatory variables in our cross-sectional regressions explaining CDS spreads.

3.1.1. *Liquidity Variables*

We construct three variables to proxy for liquidity: the Amihud illiquidity measure, the number of zero return trading days in the year, and bid-ask spreads.

The Amihud illiquidity measure is calculated as in Amihud (2002) using the following equation:

$$ILLIQ_{it} = \frac{1}{DAYS_{it}} \sum_{t=1}^{DAYS_{it}} \frac{|r_{it}|}{PRC_{it} \times VOL_{it}} \times 10^6,$$

where r_{it} is the ith stock's return for day t, PRC_{it} is closing price, and VOL_{it} is daily trading volume, that is, the number of shares traded for a firm. $DAYS_{it}$ is the number of trading days for stock i in year t. This proxy for liquidity is used by Acharya and Pedersen (2005) who develop a liquidity-extended CAPM and Avramov, Chordia and Goyal (2006) who examine the relationship of liquidity to autocorrelation in stock returns.

The number of zero return trading days in the year is a measure developed by Lesmond, Ogden and Trzcinka (1999) to measure transaction costs and is often referred to as the LOT measure. Das and Hanouna (2007) find that LOT also measures liquidity. Whether LOT measures transaction costs or liquidity is not crucial in our context since we view illiquidity as a hedging cost in managing default risk exposure. We calculate the number of zero return trading days in the year using CRSP. However, on days where no trade occurs (reported volume is zero) CRSP calculates returns from the average of the bid and ask prices. This can create circumstances where there are non-zero returns on days with no volume. To correct for this we set zero volume days to also have zero return.

The bid-ask spread is calculated following Amihud and Mendelson (1986) as the difference between the ask and bid prices on CRSP divided by the average of the two.

3.1.2. *Distance-to-Default*

As presented in equations (1), (2), (3) and (4), the stock S of a firm is a call option on it's underlying value V with an exercise price equal to the face value of debt F and a time to maturity of T. We recall the result here.

$$S = V\Phi(d_1) - e^{-rT} F \Phi(d_2) \tag{6}$$

where $\Phi(.)$ is the cumulative normal distribution function with d_1 and d_2 given by:

$$d_1 = \frac{\log(V/F) + (r + \sigma^2/2)T}{\sigma\sqrt{T}}, \quad d_2 = d_1 - \sigma\sqrt{T} \tag{7}$$

Since stock $S(V)$ is function of firm value, application of Ito's lemma allows us to express stock volatility in terms of firm volatility as follows:

$$\sigma_S = \left(\frac{V}{S}\right) \frac{\partial S}{\partial V} \, \sigma \tag{8}$$

The Merton (1974) model uses equations (6) and (8) solve for V and σ where σ_S, r, S, F, and r are obtained exogenously. T is assumed to be one year following standard practice. σ_S is the annualized standard deviation of returns and is estimated from the prior 100 trading days of stock price returns. Similar to Bharath and Shumway (2005), we require that at least 50 trading days be available for these computations. The market value of equity S is computed as the number of shares outstanding times the end of quarter closing stock price. As in Vassalou and Xing (2004), we take the face value of debt F to be debt in current liabilities (COMPUSTAT item 45) plus one-half of long-term debt (COMPUSTAT item 51). The risk-free rate r is the 3-month treasury constant maturity rate from the Federal Reserve Bank following Duffie, Saita and Wang (2007). We numerically solve the system of simultaneous equations in the Merton model to obtain the firm value V and the volatility of the firm σ. Then distance to default is computed as:

$$DD = \frac{\log(V/F) + (\mu - \sigma^2/2)T}{\sigma\sqrt{T}} \tag{9}$$

where μ is estimated as the annualized mean equity returns on the prior 100 trading days.

3.1.3. *Accounting Ratios*

We measure firm size as the value of total assets (COMPUSTAT-Quarterly item 44) divided by the Consumer Price Index for all-urban consumers, all items (Series CUUR0000SA0) with a base of 100 in the period 1982-1984. ROA is constructed as net income (item 69) divided by total assets. Interest coverage is taken as pretax income (item 23) plus interest expense (item 22) divided by interest expense, the cash-to-asset ratio is cash and equivalents (item 36) over total assets. We proxy for differences in capital structure by calculating the ratio of total liabilities (item 54) to total assets.

We account for seasonal effects by taking the trailing four-quarter average of ROA and interest coverage. The relationship between CDS spreads and interest coverage is usually monotonically increasing. When interest coverage is ample, the effect of small changes in interest coverage will be negligible. Sometimes, interest coverage is negative, and then the ratio is not meaningful since the relative magnitude of pretax income to interest expense is blurred. As undertaken by Blume, Lim, and MacKinlay (1998) we adjust the interest coverage ratio in two ways. One, before taking the trailing four quarter average, negative quarterly interest coverage ratios are set to zero. Two, trailing 4 quarter average interest coverage ratios are capped at 100, and such censoring is undertaken on the assumption that further increases in value convey no additional information. As in Blume, Lim, and MacKinlay (1998) we allow the data to determine the shape of the nonlinearity. Assume that IC_{it} is the interest coverage for firm i in quarter t, then the interest coverage ratio in the regression model is:

$$IC_{it} = \sum_{j=1}^{4} \kappa_j c_{jit} \tag{10}$$

where c_{jit} is defined in the following table as:

	c_{1it}	c_{2it}	c_{3it}	c_{4it}
$IC_{it} \in [0, 5)$	IC_{it}	0	0	0
$IC_{it} \in [5, 10)$	5	$IC_{it} - 5$	0	0
$IC_{it} \in [10, 20)$	5	5	$IC_{it} - 10$	0
$IC_{it} \in [20, 100]$	5	5	10	$IC_{it} - 20$

The result is that the regression model determines the form of the non-linearity between the dependent variable and the interest coverage ratio.

3.1.4. *Other Control Variables*

To account for differences in industry performance we include the prior year return on the industry associated with the firm. Industries are defined using the Fama and French (1997) 17-industry classification. We also include the volatility of equity used in the distance to default separately since volatility is strongly related to credit risk (Duffie, Saita and Wang (2007) include the VIX in addition to the Distance to Default measure). Note also that the Moody's Public Firm model (see Sobehart, Stein, Mikityanskaya and Li (2000)) includes equity volatility as a measure of market sensitivity.

3.2. *Empirical Results*

In Table 1 we report the descriptive statistics of the data. The variables relate to measures of both, credit and liquidity risk for individual firms. Looking at the 3 quartiles of the data in relation to the mean suggests that there are not too many outliers.

We next estimate four models of multivariate regressions. In the first three, we examine the relationship between the log of CDS spreads (in basis points) and our three measures of liquidity individually.[6] In the fourth model, we also regressed the log of CDS spreads on all three measures of liquidity in the same pooled panel regression. The results are presented in Table 2. All three metrics of illiquidity are highly significant. We used time dummies to remove time-series effects and thereby isolate the firm-specific effects. We also used firm clustered standard errors. These corrections are imposed in all subsequent analyses as well.

We then augmented the basic regressions with a credit variable and a macro-economic variable to examine the impact on the liquidity variables. The credit variable chosen was the standard measure of distance to default (DD) and the macro-economic one is the level of the three-month Treasury rate (TBILL). Both variables were successfully used in prior work by Duffie, Saita and Wang (2007). In Table 3 we see that distance to default greatly increases the explanatory power of the regression but that the Treasury rate does not. Injection of these additional variables does not render the liquidity variables insignificant at all. Only in the regression with all three variables taken together, is bid-ask spread insignificant. However, these regressions make it clear that equity market liquidity matters in explaining the cross-section of CDS spreads.

In Table 4 we provide the kitchen sink regression that contains all major credit and illiquidity variables we consider in this paper, as listed in Table 1. In the initial three models, we use each of our three liquidity metrics individually. Despite the inclusion of many credit variables, the three illiquidity variables remain strongly significant. In the fourth model, we include all three illiquidity variables together, and now bid-ask spreads are not significant, though the other two (ILLIQ and LOT) are. Therefore, there is strong statistical evidence for the impact of equity market liquidity on CDS spreads.

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[6] We use the logarithm of CDS spreads as the dependent variable because spreads are exponential functions of the state variables in the popular class of affine models. For a theoretical analysis of this, see Das, Hanouna and Sarin (2006).

Using the estimates in Table 4 we computed the percentage change in CDS spreads for a one standard-deviation change in equity market liquidity in the cross-section of firms. The impact of this magnitude of change on spreads is 5.86%, 9.48% and 16.84% respectively across the three models. If the average (across firms) time-series standard deviation is used instead of the cross-sectional standard deviation this effect on spreads is 3.30%, 4.38% and 9.82% respectively.

Finally, we consider if the impact of illiquidity on CDS spreads is greater for lower quality firms. In order to examine this, we interacted distance to default with our three liquidity variables. Firms with smaller distance to default are of poorer credit quality. Hence, a significant negative coefficient on the interaction variable will imply that liquidity impacts credit spreads more for lower credit quality firms. We find weak evidence in support of this proposition. The results are shown in Table 5. We can see that the interaction term is significant only in Model 1 (for Amihud's ILLIQ measure) and the sign is negative as required. It is insignificant in the case of the other two models. The drop in significance might be the result of constraining the model coefficients to be the same for high and low DD firms, though ILLIQ is more widely used in the liquidity literature since it is known to be a robust measure. In Model 4 in Table 5 we used all three liquidity measures and interaction terms together. Here, the ILLIQ measure swamps the others, and the interaction term is still significant. Hence, there is confirmation of the proposition that CDS spreads for low DD firms will be more impacted by equity liquidity than the spreads of high DD firms. [7]

4. Conclusion

Whereas it is widely accepted that liquidity is a major component of the spreads of corporate bonds, there is almost no literature on liquidity in CDS spreads. This paper studies whether individual firm liquidity can further explain the cross-section of CDS spreads, after controlling for default risk, using market-based and firm-specific variables. We find strong evidence that CDS spreads contain liquidity components. We used three different proxies for equity market liquidity that are commonly used in the equity literature, and roughly speaking, a one standard deviation change in the liquidity metric results in a 6% to 16% change in CDS spreads.

Our paper is also unique in that, unlike the link already made in the literature between bond spreads and *bond* market liquidity, we make the link between CDS spreads and *equity* market liquidity. We provide a theoretically supported link between equity markets and CDS spreads via the mechanism of hedging. The sign and magnitude of the liquidity effect on CDS spreads is derived analytically in the structural model framework of Merton (1974). After positing theoretically that equity market illiquidity should be a component of CDS spreads at the individual firm level, empirical analysis shows that this is indeed so at high levels of statistical significance. We further derive that the illiquidity component will increase as the credit quality of the firm declines. We run tests to affirm that this result is also supported in the data.

Using equity market proxies for liquidity has the practical benefit that plentiful data is available, which is not the case with bond market proxies. Our results imply a growing connection between the credit and equity markets, and suggest that cross-market liquidity linkages may be a good avenue for further research. Given the growing market for capital structure arbitrage, we should not be surprised to see the liquidity link become stronger with time.

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[7] As a robustness check, we redid the analyses using expected default frequency (EDF) instead of DD and found the results to be unchanged, except that the sign of the interaction term is reversed, since EDF and DD are inversely related to each other.

References

Acharya, V., and Pedersen, L., 2005. Asset Pricing with Liquidity Risk, *Journal of Financial Economics* 77(2), 375-410.

Acharya, V., Schaefer, S., Zhang, Y., 2007. Liquidity Risk and Correlation Risk: A Clinical Study of the General Motors and Ford Downgrade of May 2005, Working paper, London Business School.

Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time series effects, *Journal of Financial Markets* 5, 31-56.

Amihud, Y., Mendelson, H., 1986. Asset Pricing and the Bid-Ask Spread, *Journal of Financial Economics* 17, 223-249.

Avramov, D., Chordia, T., Goyal, A., 2006. Liquidity and Autocorrelations in Individual Stock Returns, *Journal of Finance* 61(5), 2365-2394.

Berndt, A., Douglas, R., Duffie, D., Ferguson, M., Schranz, D., 2003. Measuring Default-Risk Premia from Default Swap Rates and EDFs, Working paper, Graduate School of Business, Stanford University.

Bessembinder, H., Maxwell, W., Venkataraman, K., 2005. Market Transparency, Liquidity Externalities, and Institutional Trading Costs in Corporate Bonds, forthcoming *Journal of Financial Economics*.

Bharath, S., Shumway, T., 2005. Forecasting Default with the KMV-Merton Model, Working paper, University of Michigan.

Blume, M., Lim, F., MacKinlay, C.A., 1998. The Declining Credit Quality of U.S. Corporate Debt: Myth or Reality?, *Journal of Finance* 53, 1389-1413.

Carr, P., Wu, L., 2007. A simple robust link between American puts and credit insurance, Working paper, Baruch College.

Chacko, G., 2005). Liquidity Risk in the Corporate Bond Markets, Working paper, Harvard Business School.

Chacko, G., Jurek, J., Stafford, E., 2008. The Price of Immediacy, *Journal of Finance* 63(3), 1253 - 1290.

Chen, L., Lesmond, D., Wei, J., 2007. Corporate yield spreads and bond liquidity, *Journal of Finance* 62(1), 119-149.

Collin-Dufresne, P., Goldstein, R., Martin, J.S., 2001. The Determinants of Spread Changes, *Journal of Finance* 56, 2177-2207.

Das, S., Hanouna, P., Sarin, A., 2006. Back to Basics: Fundamentals-Based versus Market-Based Cross-Sectional Models of CDS Spreads, Working paper, Santa Clara University.

Das, S., Hanouna, P., 2007. Run Length and Liquidity, Working paper, Santa Clara University.

de Jong, F., Driessen, J., 2005. Liquidity Risk Premia in Corporate Bond Markets, Working paper, University of Amsterdam.

Downing, C., Underwood, S., Xing, Y., 2007. The Relative Informational Efficiency of Stocks and Bonds: An Intraday Analysis, Working paper, Rice University.

Duffie, D., Saita, L., Wang, K., 2007. Multiperiod Corporate Default Probabilities with Stochastic Covariates, *Journal of Financial Economics* 83, 635-665.

Ericsson, J., Renault, O., 2006. Liquidity and Credit Risk, *Journal of Finance* 61(5), 2219 - 2250.

Ericsson, J., Jacobs, K., Oviedo, R., 2005. The Determinants of Credit Default Swap Premia, forthcoming *Journal of Financial and Quantitative Analysis*.

Fama, E.F., French, K.R., 1997. Industry costs of equity, *Journal of Financial Economics* 43, 153-193.

Goldstein, M., Hotchkiss, E., Sirri, E., 2006. Transparency and Liquidity: A Controlled Experiment on Corporate Bonds, Working paper, Boston College.

Huang, J., Huang, M., 2003. How Much of the Corporate-Treasury Yield Spread is Due to Credit Risk?, Working paper, Penn State.

Leland, H., 1985. Option Pricing and Replication with Transaction Costs, *Journal of Finance* 40, 1283-1301.

Lesmond, D., Ogden, J., Trzcinka, C., 1999. A New Estimate of Transaction Costs, *Review of Financial Studies* 12(5), 1113-1141.

Longstaff, F., Mithal, S., Neis, E., 2005. Corporate yield spreads: Default risk or liquidity? New evidence from the credit default swap market, *Journal of Finance* LX, 2213-2253.

Mahanti, S., Nashikkar, A., Subrahmanyam, M., 2007. Latent Liquidity and Corporate Bond Spreads, Working paper, NYU Stern School of Business.

Merton, R.C., 1974. On the Pricing of Corporate Debt: The Risk Structure of Interest Rates, *Journal of Finance*, v29, 449-470.

Sobehart, J., Stein, R., Mikityanskaya, V., Li, L., 2000. Moody's Public Firm Risk Model: A Hybrid Approach to Modeling Short Term Default Risk, Global Credit Research, *Moody's Investors Service*.

Vassalou, M., Xing, Y., 2004. Default risk in equity returns, *Journal of Finance* 59, 831-868

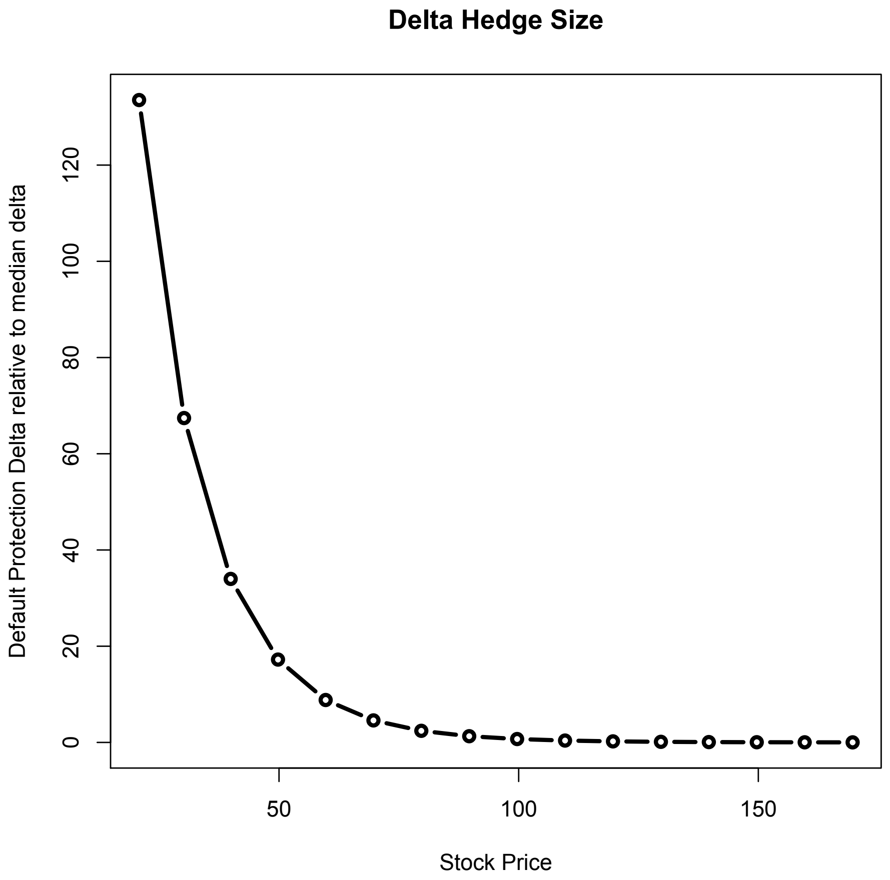

Fig. 1. Delta of the CDS. The plot shows how the delta of the CDS contract changes when the stock price changes. This plot was generated by varying firm value from 50 to 200, and computing the stock price and the delta of the CDS. We plot the delta divided by the median delta for this range of firm value, based on equation (5). The parameters of the Merton model were set to: debt face value $F = 50$, debt maturity $T = 5$ years, risk-free rate $r = 10\%$, and firm asset volatility $\sigma = 20\%$. Since CDS hedging costs are proportional to the delta of the CDS with respect to the stock price, we see that delta increases rapidly as the stock price declines, implying that poor quality firms' CDS spreads will be more sensitive to equity market illiquidity.

Table 1

Descriptive statistics. The data is taken from Bloomberg, Inc. It consists of 2,860 quarterly credit default swap spreads over the period 2001-2005. This sample was restricted to include only CDS securities where the notional value is dollar denominated and where the reference entity is a publicly traded firm. Financial information on the reference entity is then obtained from COMPUSTAT and CRSP. After filtering the data, we obtained a total of 1452 observations coming from 195 distinct firms.

VARIABLE	MNEMONIC	MEAN	MEDIAN	Q1	Q3
3 MONTH TBILL	TBILL	0.01	0.01	0.01	0.02
AMIHUD ILLIQUIDITY	ILLIQ $\times 10^4$	3.64	1.99	1.14	4.14
ZERO RETURN DAYS	LOT	2.92	2	1	4
BID-ASK SPREADS	BASPREAD $\times 10^3$	2.54	1.55	0.72	3.31
CASH/ASSET	CASH	0.06	0.04	0.01	0.08
DISTANCE TO DEFAULT	DD	9.94	9.9	6.69	13.13
EQUITY VOLATILITY	EQVOL	0.28	0.26	0.2	0.34
INTEREST COVERAGE 1	C1	3.41	3.72	2.14	5
INTEREST COVERAGE 2	C2	1.25	0	0	2.1
INTEREST COVERAGE 3	C3	1.01	0	0	0
INTEREST COVERAGE 4	C4	1.46	0	0	0
INVESTMENT GRADE DUMMY	INVGRADE	0.91	1	1	1
LIABILITIES TO ASSET	LTOA	0.67	0.68	0.58	0.77
LOG OF ASSETS	LOGASSET	4.51	4.43	3.84	5.03
LOG OF CDS SPREAD	LOGCDS	4.14	3.98	3.53	4.64
INDUSTRY RETURNS	INDRET	0	0.01	-0.02	0.03
RETURN ON ASSETS	ROA	0.01	0.01	0	0.02

Table 2

Explaining CDS spreads with liquidity variables only. In this set of regressions the dependent variable is the log of CDS spreads. The independent variables are our three measures of liquidity: Amihud (2002)'s ILLIQ metric, Lesmond, Ogden and Trzcinka (1999)'s LOT metric, and bid-ask spreads (BASPREAD). T-statistics are provided below the estimated parameters and are based on clustered standard errors. The liquidity variables are shown in bold font if they are statistically significant at the 5% level.

	MODEL1	MODEL2	MODEL3	MODEL4
INT	3.48	3.37	3.53	3.34
	19.93	15.14	17.58	17.38
ILLIQ	**648.08**			**457.25**
	4.85			2.88
LOT		**0.09**		**0.05**
		5.35		2.95
BASPREAD			**146.27**	**56.54**
			6.99	1.97
R-SQUARE	0.16	0.04	0.18	0.24
N	1452	1452	1452	1452

Table 3
Explaining CDS spreads with liquidity variables augmented by primary credit and macro-economic variables. In this set of regressions the dependent variable is the log of CDS spreads. The independent variables are our three measures of liquidity: Amihud (2002)'s ILLIQ metric, Lesmond, Ogden and Trzcinka (1999)'s LOT metric, and bid-ask spreads (BASPREAD). The set of independent variables is augmented with distance to default (DD) as a credit proxy and the 3-month Treasury rate (TBILL) as a macro-economic proxy. These variables were chosen based on the work of Duffie, Saita and Wang (2007). T-statistics are provided below the estimated parameters, and are based on clustered standard errors. The liquidity variables are shown in bold font if they are statistically significant at the 5% level.

	MODEL1	MODEL2	MODEL3	MODEL4
INT	4.97	5.03	5.04	4.82
	48.10	56.86	50.6	51.53
DD	-0.09	-0.1	-0.09	-0.09
	-17.21	-19.53	-16.25	-17.48
TBILL	-3.49	-4.73	-4.6	-2.77
	-1.09	-1.39	-1.38	-0.88
ILLIQ	**426.76**			**332.32**
	4.43			3.09
LOT		**0.07**		**0.05**
		5.25		3.82
BASPREAD			**39.13**	9.48
			4.18	0.88
R-SQUARE	0.47	0.46	0.43	0.49
N	1452	1452	1452	1452
CLUSTERS	195	195	195	195

Table 4
Explaining CDS spreads with liquidity variables augmented by all credit and macro-economic variables. In this set of regressions the dependent variable is the log of CDS spreads. The independent variables are our three measures of liquidity: Amihud (2002)'s ILLIQ metric, Lesmond, Ogden and Trzcinka (1999)'s LOT metric, and bid-ask spreads (BASPREAD). The set of independent variables is augmented with all the variables from Table 1. Time dummies are used in the regressions to remove effects that are not firm-specific. T-statistics are provided below the estimated parameters and are based on clustered standard errors. The liquidity estimates are shown in bold font if they are statistically significant at the 5% level.

	MODEL1	MODEL2	MODEL3	MODEL4
INT	4.00	4.19	4.31	3.93
	9.68	10.72	11.31	9.27
DD	-0.03	-0.04	-0.03	-0.03
	-4.67	-4.92	-5.07	-4.88
LTOA	0.78	0.87	0.85	0.79
	3.05	3.24	3.18	3.10
CASH	0.04	-0.09	0.00	0.00
	0.09	-0.22	0.00	0.00
ROA	-1.93	-1.96	-1.83	-1.86
	-3.40	-3.50	-3.30	-3.43
EQVOL	1.90	2.02	1.81	1.88
	6.90	6.82	6.16	6.86
C1	-0.10	-0.11	-0.12	-0.10
	-4.41	-4.96	-5.43	-4.37
C2	0.00	0.01	0.01	0.01
	0.11	0.50	0.35	0.33
C3	0.00	0.00	0.00	0.00
	0.04	-0.41	0.16	-0.20
C4	-0.01	-0.01	-0.01	-0.01
	-2.35	-2.05	-2.14	-2.35
INVGRADE	-0.84	-0.84	-0.86	-0.85
	-10.68	-10.79	-11.69	-10.82
LOGASSET	0.05	-0.01	0.00	0.04
	0.98	-0.24	0.03	0.82
INDRET	0.87	0.84	0.84	0.78
	1.73	1.62	1.61	1.58
ILLIQ	**284.90**	.	.	**193.11**
	3.90			2.42
LOT	.	**0.04**	.	**0.03**
		3.73		2.54
BASPREAD	.	.	**55.58**	22.19
			4.41	1.46
RSQUARE	0.69	0.69	0.69	0.70
N	1452	1452	1452	1452
CLUSTERS	195	195	195	195

Table 5

Impact of liquidity on spreads based on varying credit quality. Low distance to default firms are of poorer quality than firms with high distance to default. We interacted DD with the illiquidity variable to see if it was significant. T-statistics are presented below the estimates and are based on clustered standard errors and time dummies are used to isolate the firm-specific effect from time-series effects. The ILLIQ variables is Amihud's illiquidity for Model 1, the LOT measure for Model 2, and bid-ask spreads for Model 3. Model 4 puts all the illiquidity measures in one regression with individual interaction terms. Significant (at the 5% level) illiquidity coefficients are highlighted in bold font.

	MODEL 1	MODEL 2	MODEL 3	MODEL 4
INT	4.01	4.17	4.28	3.91
	9.68	10.76	11.27	9.44
DD	-0.03	-0.03	-0.04	-0.04
	-4.20	-4.06	-5.17	-4.60
LTOA	0.78	0.86	0.86	0.81
	3.04	3.20	3.21	3.15
CASH	0.06	-0.09	-0.01	0.02
	0.14	-0.20	-0.02	0.04
ROA	-1.96	-1.97	-1.84	-1.93
	-3.46	-3.51	-3.29	-3.55
EQVOL	1.85	2.01	1.87	1.94
	6.78	6.81	6.46	7.27
C1	-0.10	-0.11	-0.12	-0.10
	-4.33	-4.92	-5.41	-4.22
C2	0.00	0.01	0.01	0.01
	0.05	0.47	0.38	0.29
C3	0.00	0.00	0.00	0.00
	0.09	-0.40	0.18	-0.13
C4	-0.01	-0.01	-0.01	-0.01
	-2.52	-2.04	-2.09	-2.52
INVGRADE	-0.84	-0.84	-0.85	-0.84
	-10.84	-10.79	-11.26	-10.70
LOGASSET	0.05	-0.01	0.00	0.04
	0.88	-0.25	0.09	0.79
INDRET	0.94	0.84	0.77	0.79
	1.88	1.62	1.43	1.60
ILLIQ	**367.91**			**343.35**
	4.97			3.64
LOT		**0.05**		0.02
		2.22		0.79
BASPREAD			**49.17**	4.22
			3.93	0.27
DD*ILLIQ	**-12.86**			**-19.95**
	-1.92			-3.02
DD*LOT		0.00		0.00
		-0.53		0.81
DD*BASPREAD			2.22	3.16
			1.26	1.78
R-SQUARE	0.70	0.69	0.69	0.70
N	1452	1452	1452	1452
CLUSTERS	195	195	195	195